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Optimization model construction of cross-border e-commerce logistics network in countries along the Belt and Road route

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SUMMARY: *The deepening impact of the "Belt and Road" on the opening-up and trade development of the countries along the route has put forward higher requirements for cross-border logistics and transportation of e-commerce enterprises. In this paper, enterprise A is selected as an example object of analysis, and the Improved Adaptive Genetic Algorithm (IAGA) is used to optimize the cross-border e-commerce logistics network, realize the rational planning of the cross-border e-commerce logistics network, reduce the cost of cross-border e-commerce logistics enterprise logistics and transportation, improve the efficiency of resource utilization, and enhance the timeliness of logistics and transportation. The study shows that IAIGA can solve the problem of lack of dynamic adaptability existing in IGA, with faster convergence speed, better convergence stability, higher optimization accuracy, and can provide technical support for solving parameter identification problems. Meanwhile, the constructed optimization model and the designed improved genetic algorithm IAIGA to solve the cross-border e-commerce logistics network optimization problem are feasible and effective, and the relative error rate of IAIGA algorithm is no more than 1.8%, which can reduce the logistics and transportation cost of enterprises by 1%~8%.*

KEYWORDS: *belt and road; cross-border e-commerce; logistics network optimization; optimization model; improved adaptive genetic algorithm*

1 Introduction

In the wave of digitalization sweeping the world, cross-border e-commerce is reshaping the international trade pattern [1]. In this process, the countries along the Belt and Road, with their unique geographic location and abundant resource advantages, have become the "potential blue ocean" of cross-border e-commerce, attracting countless cross-border enterprises with their potential value and development space in the market [2]. Undeniably, the strategic position of the countries along the Belt and Road has made their importance in international trade increasingly significant, and promoted the gradual release of huge market potential. However, the lagging logistics network has seriously limited its development, and problems such as inefficient transportation and high cost need to be solved [3]. The new era calls for innovation and breakthrough, how to optimize the cross-border e-commerce logistics network, to achieve the leap of cross-border trade between the countries along the Belt and Road, has become a key issue in front of the industry at present.

In recent years, many scholars have elaborated their opinions on the development of cross-border e-commerce, and some scholars have expressed their views on the development of cross-border e-commerce logistics. Aydın and Savrul studied the relationship between globalization

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and cross-border e-commerce by taking Turkey as an object, and pointed out that in the process of globalization, the development of communication technology, the decline of transportation costs and the reduction of trade barriers have brought an important impact on the development of cross-border trade [4]. Zhu et al. developed a three-stage model to assess the impact of product awareness on cross-border e-commerce purchase intention using Hierarchy of Effects Model and Commitment Engagement Theory, and the analysis showed that product description and product awareness had a positive impact on trust, whereas platform enduring engagement and platform situational engagement both positively impacted trust [5]. Taking Alibaba as an example, Kwak et al. studied the development of cross-border e-commerce platforms and the construction of the rule of law in China, exploring the relationship between various kinds of legitimacy and acceptance from the perspectives of market legitimacy, relational legitimacy, and social legitimacy, and pointing out that the cross-border e-commerce platforms should put more attention on establishing legitimacy among the stakeholders [6]. Giuffrida et al. reviewed the contribution of cross-border e-commerce to China in the field of logistics with an eye to the role played by other countries in the Greater China region in this complex process. The main objective is to outline future research directions that encourage the development of CBEC [7]. Valarezo et al. examined the drivers and barriers to cross-border e-commerce using the standard neoclassical utility maximization framework and logistic regression techniques with consumers in Spain and found that males, education, computer and Internet skills, and customer reviews were influences on cross-border e-commerce trade, and discussed measures of Internet trust and the use of online information review for goods and services [8].

With the in-depth research on cross-border e-commerce, many scholars have found that cross-border e-commerce logistics and distribution has a development lag and needs more policy support and model innovation. For example, Hsiao et al. studied cross-border e-commerce logistics service design based on text mining, and proposed a method using partial least squares to analyze the elements of customers' emotional perceptions of services and products, and provided complementary cross-border e-commerce logistics service design through online content mining [9]. Gessner and Snodgrass propose to design a cross-border e-commerce distribution network for SMEs by combining Canadian and U.S. incentive programs, pointing out that there are logistical, tariff, and legal barriers to cross-border e-commerce business, and exploring the transactional potential for cross-border e-commerce trade between Canada and the U.S. [10]. Wei and Dong studied the cross-border logistics network between the countries along the Belt and Road, which connects the maritime logistics network with the inland cross-border logistics network through dry ports, and investigated the organizational optimization problem of inland import and export goods under different network scenarios by applying the network, and proposed a bi-objective mixed integer programming model using adaptive weighted genetic algorithm (awGA) as the solution method [11]. Lu et al. investigated the multimodal transportation network problem under uncertainties, considering various uncertainties such as freight volume, cost, time and carbon emissions, and used Monte Carlo simulation to optimize the strategy of multimodal transportation paths and logistic transport modes [12]. Barenji et al. proposed a hybrid agent-based approach for scheduling and synchronization of cross-border e-commerce logistics parks (EcLP). The proposed platform is developed based on an agent-based technology that is not only used for decentralization and synchronization purposes but has been optimized for transportation and logistics of the entire system [13].

Cross-border logistics network layout involves many factors, often because the path cost, overseas warehouse location issues, upfront investment costs, commodity stagnation costs, return and exchange costs, timeliness, customer satisfaction and other factors make the logistics network very complex [14, 15]. As a result, its cross-border e-commerce logistics network optimization problems often contain multi-dimensional objectives and multiple variables at the same time, which essentially belongs to NP problems [16]. As the objective space and the number of variables are raised, the number of solutions also increases massively, and the difficulty of another solution increases greatly [17]. Therefore, multi-objective network optimization algorithms must be sought to solve it. Regarding the research on multi-objective optimization of cross-border logistics network, Wenya and Ze used the multi-objective optimization method to optimize the e-commerce logistics end distribution network, and analyzed the influence of factors on the optimization of cross-border e-commerce logistics end distribution network of biotechnology products by constructing a model with the objective of minimizing economic cost and optimal path of distribution vehicles; at the same time, the ant colony algorithm was utilized to have the advantages of positive feedback characteristic and convergence speed advantage of ACO algorithm to solve the model [18]. Li and Wan modeled the logistics and distribution network design as a multi-objective optimization model, and in order to cope with the complex and dynamic multi-dimensional objective optimization problem, genetic neural networks were applied to the distribution optimization that simultaneously considered multiple factors such as logistics cost, customer satisfaction, logistics time cost, and so on [19]. Li proposed a cross-border e-commerce logistics network optimization strategy based on the ADASYN algorithm, and the experimental results show that the strategy can significantly improve the performance indicators of cross-border e-commerce logistics services, and the optimized logistics time is shortened by 40%, the logistics cost is reduced by 40%, and the distribution efficiency is improved by 8% [20].

Regarding the optimization of the location selection for cross-border logistics networks, Xie et al. proposed a multi-objective hub location model that integrates two innovative indicators (hub network utilization rate and hub economic stimulation effect). This model was solved using the non-dominated sorting genetic algorithm III (NSGA-III) with a training population, and ultimately a Pareto optimal solution set consisting of 44 international logistics hubs across Asia, Europe, West Africa, Oceania, and Central America was obtained [21]. Shi combines the concept of intelligent strategy to systematically optimize the stages of e-commerce logistics distribution, such as warehousing and sorting, trunk transportation and end distribution, aiming to achieve the goals of reducing end distribution costs, improving distribution efficiency, and increasing customer satisfaction [22]. Pan, S and Cheng proposed a shortest path optimization algorithm for domestic and international e-commerce logistics based on two-way search. The algorithm sets collaborative parameters based on the shortest path, constructs an adaptive domestic and international e-commerce logistics path grid planning optimization model, and further integrates particle swarm algorithm and genetic algorithm to establish a logistics path planning model [23]. In order to reduce the cost of cross-border e-commerce logistics site selection, Shen proposed a multi-logistics site selection method based on return uncertainty, which takes the minimization of site construction cost, transportation cost, return cost and operation cost as the objective function, and the return recovery cost and delayed pickup time as the constraints of the site selection model, and uses the improved chicken swarm algorithm based on simulated annealing for cross-border e-commerce multi-logistics site selection model to solve the model [24]. Liu et al. combined the Internet of networking data fusion technology to determine the optimization level of logistics path for different priority indicators, selected the constraint function to divide the optimization level, combined the optimization objective with the fitness function, and determined the optimization order through the objective solution to achieve the optimization of cross-border e-commerce logistics path [25]. Based on the ELECTRE method system, Nie proposed a multi-attribute decision-making method applicable to the selection of cross-border e-commerce logistics and transportation modes, which can effectively help cross-border e-commerce companies to select the appropriate logistics and transportation modes according to the characteristics of the goods [26]. Fu proposed a cross-border e-commerce logistics distribution path optimization method based on improved genetic algorithm, which combines the improved genetic algorithm to regulate the distribution parameter variables and effectively select the optimal distribution path based on the results of arithmetic operations, so as to realize the effective optimization of cross-border e-commerce logistics distribution path [27].

In this paper, for the optimization problem of cross-border e-commerce logistics network in the countries along the Belt and Road, an optimization model is constructed, and the adaptive genetic algorithm IAGA, which introduces the diversity of the immune system population for improvement, is designed, and the IAGA algorithm is used to solve for the optimal value of the objective function of the model. In order to verify the effectiveness of the constructed optimization model and the proposed solution algorithm IAGA, this paper selects the cross-border e-commerce logistics network of enterprise A as an example research object, and carries out the optimization simulation experiment using six groups of benchmark functions, compares the solution results of IAGA and AGA, and compares the solution results of IAGA with the actual value of enterprise A.

2 Optimization model of cross-border e-commerce logistics network in countries along the “Belt and Road”

Aiming at the optimization problem of cross-border e-commerce logistics network in countries along the Belt and Road, this paper focuses on the optimization model construction of cross-border logistics paths and multimodal transport modes, and uses the improved adaptive genetic algorithm (IAGA) to solve the model.

2.1 Analysis of Influencing Factors of Cross-border E-commerce Logistics Paths

The content of this chapter studies the rational adoption of cross-border e-commerce logistics paths and multimodal transport modes under the multimodal transport mode of public railway, sea and air transport, with the main goal of maximizing the benefits of the organization's cross-border e-commerce logistics network optimization objectives. When making cross-border e-commerce logistics path and multimodal transportation mode selection, the influence of the following factors is mainly considered:

(1) Logistics cost. The costs in cross-border e-commerce logistics transportation mainly include transportation costs and transit costs. Among them, the transportation cost is mainly the transportation cost incurred by the transportation means to transport the goods.

(2) Logistics time. Logistics time generally includes transportation time and storage time generated by storing goods at seaports, dry ports or airports.

(3) Carbon emission. When organizing cross-border e-commerce logistics, different transportation means under different multimodal transport modes will generate different amounts of carbon emissions.

(4) Cross-border e-commerce logistics transportation network capacity. The transportation network capacity of cross-border e-commerce logistics mainly includes the transportation capacity of each cross-border e-commerce logistics path under the multimodal mode and the transshipment capacity of transshipment hub ports.

2.2 Cross-border e-commerce logistics path optimization model construction

2.2.1 Abstract description of cross-border e-commerce logistics and transportation problems

Cross-border e-commerce logistics and transportation consists of different types of cargo transportation main bodies, so as to realize the transportation process of goods from the source to the destination. Therefore, in the original cross-border e-commerce logistics and transportation problem, the addition of China's domestic airports and China's foreign airports. The abstract description of the “Belt and Road” cross-border e-commerce logistics transportation network after the addition of air transportation is shown in Figure 1. Different symbols in the figure indicate different types of cargo transportation locations, in which, increasing the cargo transportation location of China's internal airports $a(a \in A)$ and China's external airports $a'\left(a' \in A'\right)$, accordingly Air transportation mode of transportation was added. Multiple paths of multimodal transportation of transported goods are generated by means of connections between different transport locations.

As can be seen from Figure 1, the cross-border transportation of goods from the domestic source i to the destination j outside China, in addition to the three multimodal modes of road-seaport, road-railway-seaport, and road-railway, a new multimodal mode has been added: through the use of road transportation of goods from the domestic source i transported to reach the Chinese internal airports a, and then through air transportation to reach the Chinese then by air transportation to China's outer airports a', and finally to reach the destination outside China j is relying on road transportation, i.e., multimodal transportation mode of public aviation.

The four intermodal transport modes include the optimization of cross-border e-commerce logistics paths, and the same way to find out an optimal cross-border e-commerce logistics transport path, to achieve the optimization of logistics costs, logistics time and carbon emissions of multiple objectives.

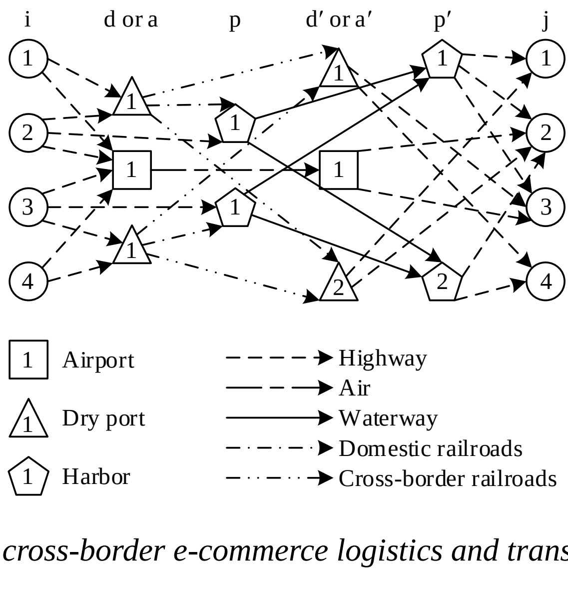


Figure 1: Description of cross-border e-commerce logistics and transportation issues

2.2.2 Parameters and variables of the model

Set the following decision variables on whether different intermodal transportation modes are adopted or not, and all the decision variables are composed of 0-1 variables, representing which intermodal transportation mode is adopted for each route, and only one intermodal transportation mode can be adopted for each route. All decision variables include the intermodal transportation mode decision variable $X_{ipp'j}$, the intermodal transportation mode decision variable $X_{idpp'j}$, and the intermodal transportation mode decision variable $X_{idd'j}$. When the variable takes 1, it means that the intermodal transportation mode is adopted and vice versa. In addition, relevant parameters need to be selected as shown below:

(1) Unit freight cost: including road unit transportation cost c_{rd}, rail unit transportation cost c_{rl}, waterway unit transportation cost c_{sea}.

(2) Carbon emission: including carbon emission factor of road transportation unit co_{rd}, carbon emission factor of railroad transportation unit co_{rl}, carbon emission factor of waterway transportation unit co_{sea}, carbon tax value r_e.

(3) Transportation distance: This includes the road transportation distance between the domestic source location i in China and the inland port d, l_{id}; the road transportation distance between the domestic source location i and the inland seaport p in China, l_{ip}; the road transportation distance from the foreign seaport p' to the foreign destination j in China, $l_{p'j}$; the road transportation distance from the foreign land port d' to the foreign destination j in China, $l_{d'j}$; the railway transportation distance from the inland port d to the inland seaport p in China, l_{dp}; the railway transportation distance from the inland port d to the foreign land port d' in China, $l_{dd'}$; and the water transportation distance from the seaport p to the foreign seaport p' in China, $l_{pp'}$.

(4) Fixed costs: These include the fixed costs for the land port d to provide the transfer service, F_d, and the fixed costs for the seaport p to provide the transfer service, F_p, respectively.

(5) Cargo Volume: Including cargo volume q_{ij} and cargo volume discount factor $B[m]$ between source i and destination j.

(6) Cargo stowage time: including cargo stowage time t_p at China's inland seaports p, cargo stowage time t_d at China's inland ports d, cargo stowage time $t_{d'}$ at China's outland ports d', and cargo stowage time $t_{p'}$ at China's outland seaports p'.

(7) Transportation speed: Includes rail unit transportation speed v_{rl}, waterway unit transportation speed v_{sea}, and road unit transportation speed v_{rd}.

Based on the above parameters, additional variables related to air transportation are added. The decision variable for the multimodal transport mode of public air transportation $X_{iaa'j}$ consists of 0-1 variables. The value of this variable is 1 when this multimodal transport mode is adopted, and 0 otherwise. The unit cost of air transportation is c_{ra}, the unit carbon emission factor of air transportation co_{ra}, the fixed cost provided by the airport a for services F_a, the storage time of goods at the domestic airport a in China t_a, the storage time of goods at the foreign airport a' outside China $t_{a'}$, the flight distance from domestic airport a to foreign airport a' in China $l_{aa'}$, and the air transportation speed v_{ra}.

2.2.3 Objective function of the model

The dual-objective mixed-integer programming model for cross-border logistics path optimization includes two objective functions: cross-border logistics cost and cross-border logistics time.

(1) Logistics cost objective function:

$$\begin{aligned}\min f_1 = & \sum_{i,j,p,p',a,a',d,d'} q_{ij} X_{ipp'j}\left(\left(C_{rd} + co_{rd} \times r_e\right)\left(l_{ip} + l_{p'j}\right) + \left(C_{sea} + co_{sea} \times r_e\right) l_{pp'}\right) \\ & + \sum_{i,j,d,p,p'} X_{idpp'j}\left(q_{ij}\left(C_{rd} + co_{rd} \times r_e\right) l_{id} + \left(C_{sea} + co_{sea} \times r_e\right) l_{pp'}\right. \\ & \left. + \left(C_{rd} + co_{rd} \times r_e\right) l_{p'j}\right) + q_{ij} B[m]\left(co_{rt} + co_{rl} \times r_e\right) l_{dp}\Big) \\ & + \sum_{i,j,d,d'} X_{idd'j}\left(q_{ij}\left(C_{rd} + co_{rd} \times r_e\right)\left(l_{id} + l_{d'j}\right) + q_{ij} B[m]\left(co_{rl} + co_{rl} \times r_e\right) l_{dp}\right) \\ & + \sum_{i,j,a,a'} q_{ij} X_{iaa'j}\left(\left(C_{rd} + co_{rd} \times r_e\right)\left(l_{ia} + l_{a'j}\right) + \left(C_{ra} + co_{ra} \times r_e\right) l_{aa'}\right) \\ & + \sum_{a,d,p} q_{ij} X_{iaa'j}\left(y_d F_d + y_a F_a + y_p F_p\right)\end{aligned} \tag{1}$$

The first and fourth parts of the cross-border logistics cost objective function represent the transportation cost and carbon tax cost of the intermodal highway-sea mode and the intermodal highway-air mode, respectively. The second and third parts represent the transportation cost and carbon tax cost of the scale-efficient intermodal rail-sea intermodal mode and the intermodal rail-multimodal mode, respectively. The last part is the fixed cost of transshipment work performed by each intermodal mode.

(2) Logistics time objective function:

$$\begin{aligned}\min f_2 = \Bigg(& \sum_{a,a',dd',p,p'} X_{ipp'j}\left(\left(l_{ip} + l_{p'j}\right)/v_{rd} + l_{pp'}/v_{sea} + t_p + t_{p'}\right) \\ & + X_{idpp'j}\left(\left(l_{id} + l_{p'j}\right)/v_{rd} + l_{dp}/v_{rl} + l_{pp'}/v_{sea} + t_p + t_p + t_{p'}\right) \\ & + X_{idd'j}\left(\left(l_{id} + l_{d'j}\right)/v_{rd} + l_{dd'}/v_{rl} + t_d + t_{d'}\right) \\ & + X_{iaa'j}\left(\left(l_{ia} + l_{a'j}\right)/v_{ra} + l_{aa'}/v_{rl} + t_a + t_{a'}\right)\end{aligned} \tag{2}$$

The four components of the cross-border logistics time objective function represent the stacking time in different ports at home and abroad in the transportation time of the intermodal mode of high seas, intermodal mode of high rail and sea, intermodal mode of high rail and sea, intermodal mode of high rail and high air and intermodal mode of high air, respectively. The transportation time is in days as a unit.

(3) Constraints:

$$\sum\nolimits_{d,a,p,d',a',p'}\left(X_{ipp'j} + X_{idpp'j} + X_{idd'j} + X_{iaa'j}\right) = 1, \forall i \in I; j \in J \tag{3}$$

$$X_{iaa'j} \le y_a, \forall i \in I; j \in J; a \in A; a' \in A' \tag{4}$$

$$X_{iaa'j} \in \{0,1\} \tag{5}$$

$$X_{idd'j} \le y_d, \forall i \in I; j \in J; d \in D; d' \in D' \tag{6}$$

$$X_{ipp'j} \le y_p, \forall i \in I; j \in J; p \in P; p' \in P' \tag{7}$$

$$X_{idpp'j} \le y_p, \forall i \in I; j \in J; p \in P; p' \in P'; d \in D \tag{8}$$

$$X_{idpp'j} \le y_d, \forall i \in I; j \in J; p \in P; p' \in P'; d \in D \tag{9}$$

where equation (3) indicates that transportation from the source i to the destination j can only use one of the four intermodal modes of intermodal transportation. Eq. (4) indicates that only the corresponding air port is selected to generate a multimodal mode of public transportation through that port. Eq. (5) indicates that the variables are all 0-1 variables. Eqs. (6) to (9) indicate that only the corresponding port is selected to generate an intermodal mode through that port.

2.3 Model solving based on improved adaptive genetic algorithm

In this paper, Improved Adaptive Genetic Algorithm (IAGA) is used to solve the cross-border e-commerce logistics path optimization model, and the flow of IAGA algorithm is shown in Fig. 2.

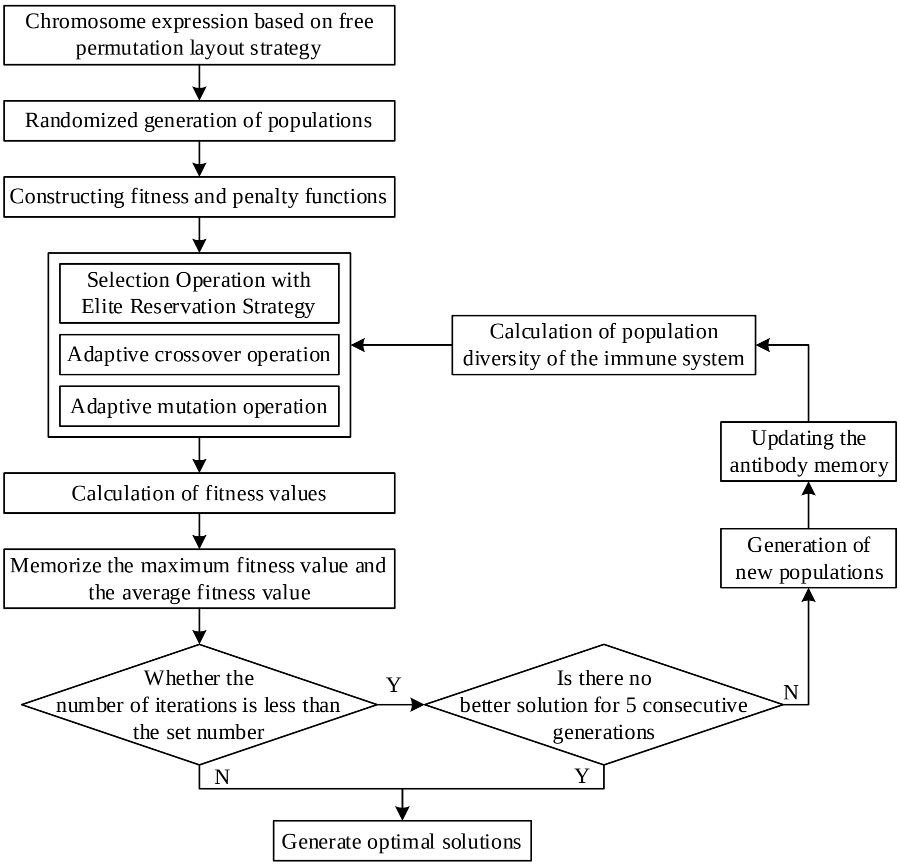


Figure 2: Flowchart of the IAGA algorithm

2.3.1 Chromosome expression

The free path planning strategy is characterized by uncertainty in both the number of cargo transportation subjects and the number of cargoes to be transported by each subject, so the corresponding chromosome expression is designed:

$$v=\left[\{m_1,m_2,\cdots,m_n\},\{a_1,a_2,\cdots,a_{n-1}\},\{\Delta_1,\Delta_2,\cdots,\Delta_n\}\right] \tag{10}$$

where: m_i is the number of the cargo transportation subject i. a_i is the branch location of the cargo transportation subject i, which takes the value of 0-1 binary code. Δ_i is the net spacing between subject i and neighboring subjects $i-1$.

An example of the location code, branch code and net spacing code of the cargo transportation body is shown in Figure 3.

Take the subject of goods transportation i as an example

Position Code: 1 2 3 | 4 5 | 6 7

Branch location code: 0 0 1 0 1 0

Net spacing code: $\Delta_1\Delta_2\Delta_3\Delta_4\Delta_5\Delta_6\Delta_7$

Figure 3: Example of location coding, line coding and net spacing coding

2.3.2 Population generation

(1) Randomly generate n codes between $1-n$ as values for the chromosome genes in the t position coding portion of the cargo transportation subject to generate a single cargo transportation subject position code of length n. Similarly, a branching code of $n-1$ length for the cargo transport subject and a net spacing code of n length for the cargo transport subject are randomly generated, and the three parts together form a chromosome of length $3n-1$.

(2) Repeat (1) until the number of chromosomes generated meets the population size.

2.3.3 Adaptation and Penalty Function Construction

In genetic algorithms the larger the fitness of an individual the better, while the cargo transportation path planning problem is the smaller the objective function the better, so the fitness function for path planning represented by the vth individual is:

$$eval\left(T_v\right)=1/W_{tv}, v=1,2,\cdots,pop\_size \tag{11}$$

where: T_v is the individual v in the Tth generation, W_{tv} is the value of the objective function of the individual v.

Due to the existence of net spacing and net row spacing of the cargo transportation body, the equipment will not overlap in both X and Y axis directions, so it is only necessary to design the penalty function of the cargo transportation body exceeding the distance in the length and width direction, i.e.:

$$\lambda_{1v} = \begin{cases} 0, & l_{v\max} \leqslant L \\ \alpha\left(l_{v\max} - L\right), & l_{v\max} > L \end{cases} \tag{12}$$

$$\lambda_{2v} = \begin{cases} 0, & h_{v\max} \leqslant W \\ \beta\left(h_{v\max} - W\right), & h_{v\max} > W \end{cases} \tag{13}$$

$$l_{v\max} = x_{vb} - x_w, w_{v\max} = y_{vb} - y_{va} \tag{14}$$

In the formula: λ_{1v} represents the penalty function for the deviation of individual v in the X axis direction, λ_{2v} represents the penalty function for the deviation of individual v in the Y axis direction, $l_{v\max}$ and $w_{v\max}$ are the maximum lengths of individual v in the X and Y axis directions respectively, and α and β are both penalty factors.

In order to ensure the diversity of the population at the early stage of evolution and accelerate the elimination of incomprehensible individuals at the late stage of evolution, the penalty factor in this paper is designed as a function that grows exponentially with the number of generations, i.e.:

$$\alpha = \theta^{T-1}\alpha_0, \beta = \theta^{T-1}\beta_0 \tag{15}$$

where: α_0 and β_0 are both initial values of the penalizing factor, and θ is the number of normals for >1.

Therefore, the fitness function with the addition of the penalty term is:

$$eval\left(T_v\right) = 1/\left(W_{tv} + \lambda_{1v} + \lambda_{2v}\right) \tag{16}$$

2.3.4 Genetic manipulation

The selection operation partially uses roulette selection with elite retention strategy. Firstly, the individuals of the population are ranked in terms of their fitness values, the individuals with the highest fitness values do not participate in the roulette and go directly to the next generation, and the rest of the individuals participate in the selection according to the roulette.

The chromosome is composed of 3 parts, and the corresponding crossover operator needs to be designed according to the characteristics of each part of the encoding. Cargo transportation body location coding and branch location coding use single-point crossover operation, and net spacing coding uses arithmetic crossover operation.

Suppose the net spacing sequence of 2 parent individuals for transportation path planning:

$$\left\{\Delta_1^A, \Delta_2^A, \cdots, \Delta_n^A\right\}, \left\{\Delta_1^B, \Delta_2^B, \cdots, \Delta_n^B\right\} \tag{17}$$

Then the net spacing of the offspring individuals is:

$$\Delta_i^{A'} = \varphi\Delta_i^A + (1-\alpha)\Delta_i^B \tag{18}$$

$$\Delta_i^{B'} = \varphi\Delta_i^B + (1-\alpha)\Delta_i^A \tag{19}$$

where: $\varphi = 1 - 0.9^{\mathrm{T}}, \varphi \in (0,1)$.

Similarly, it is necessary to design the corresponding mutation operator according to the characteristics of each part of the encoding. The cargo transportation subject position coding part adopts reciprocal mutation operation, i.e., exchanging the position of the cargo transportation subject in the sequence, which can avoid the generation of illegal coding strings. The branch position coding part of the cargo transportation body randomly selects a certain gene position, and takes the inverse operation to get different codes. The net spacing coding part of the cargo transport body is finely adjusted by using the neighborhood search technique. The process is as follows:

(1) According to the probability of variation, select the variant individual, if the net spacing part of the cargo transportation body of the selected individual is coded as: $\{\Delta_1, \Delta_2, \cdots, \Delta_i, \cdots, \Delta_n\}$.

(2) Let N be a given positive integer to generate $2N$ fields of the selected gene:

$$\Delta_{i1} = j\Delta_i / N,\ j = 1, 2, \cdots, 2N \tag{20}$$

(3) Calculate the fitness values of all neighboring individuals and retain the individual with the highest fitness value.

2.3.5 Improved Adaptive Genetic Algorithm Parameter Tuning

Population diversity formula for the immune system:

$$H(M) = \frac{1}{n}\sum_{j=1}^{n}\sum_{i=1}^{s} -P_{ij}\ln P_{ij} \tag{21}$$

where: M is the number of antibodies, n is the number of gene loci of the antibody; s is the number of mutually unequal gene characteristic values on the j th gene, and P_{ij} is the probability that the allele of the i th antibody appears on the j th gene. If the alleles of all antibodies on the j th gene are identical, $H_j(M) = 0$. If the alleles of all antibodies are identical at all loci, $H(M) = 0$. Thus, when the population converges $H(M) \to 0$; when the population diverges $H(M) \to 1$.

IAGA introduces this property of $H(M)$ by adaptively adjusting P_c and P_m through changes in $H(M)$ at different stages of evolution. i.e:

$$P_c = \begin{cases} k_1\left|\dfrac{F_{\max} - F'}{F_{\max} - F_{avg}} - \sin\left(\dfrac{\pi}{2}H(M)\right)\right| & F' \geqslant F_{avg} \\ k_3, & F' < F_{avg} \end{cases} \tag{22}$$

$$P_m = \begin{cases} k_2\left|\dfrac{F_{\max} - F}{F_{\max} - F_{avg}} - \sin\left(\dfrac{\pi}{2}H(M)\right)\right| & F \geqslant F_{avg} \\ k_4, & F < F_{avg} \end{cases} \tag{23}$$

The improvement of IAGA is aimed at individuals whose fitness value is higher than the average fitness value during genetic manipulation. At the early stage of evolution, the population diversity is rich, $H(M) \to 1$, at this time, the individuals with low fitness value P_c and P_m are lower, to avoid their damage to the good individuals. While individuals with high fitness P_c and P_m are higher, good genes can recombine to form better individuals. As evolution proceeds, the difference between individual genes becomes smaller and smaller, and $H(M)$ becomes smaller and smaller. At this time, individuals with low fitness P_c and P_m become higher, generating a large number of new individuals, increasing the diversity of the population, and preventing the algorithm from falling into a local optimum, while on the other hand, individuals with high fitness P_c and P_m become lower, and good genes of the good individuals are protected. In the late stage of evolution, the individuals almost differ from each other, and the population gradually converges, $H(M) \to 0$, at this time, the IAGA algorithm and adaptive genetic algorithm (AGA) have the same evolutionary idea.

3 Example analysis of cross-border e-commerce logistics network optimization problems of enterprise A

3.1 Introduction to Enterprise A

A Enterprise is a technology company serving global cross-border e-commerce, which is committed to providing customers with logistics, finance, big data and other multifaceted service products through market analysis, system development and resource integration, so as to provide high-quality, full-service solutions for global cross-border e-commerce.

Founded in 2018, Enterprise A is jointly established by an industry fund, one of the leading institutions in China's private equity investment field, and a global e-commerce pioneer enterprise platform, which has very rich logistics service experience and customer market resources, aiming to provide fast, stable, cost-leading, visible and sustainable logistics services for seller customers, so that buyer customers can enjoy a more high-quality and intimate service experience.

The products and services of Enterprise A mainly include international direct mail parcel service, overseas warehouse headway service, interventional supply chain platform service and credit financing products, etc., of which international direct mail parcel service is the core service product of Enterprise A, accounting for about 72% of its annual sales. The international direct mail parcel service is jointly created by the global e-commerce enterprise platform and the logistics strategic partner Enterprise A. Based on the logistics policy of the global e-commerce platform, it is a tailor-made international logistics solution for cross-border export e-commerce sellers of the Greater China region on the global e-commerce platform.

3.2 Experimental analysis of IAGA algorithm simulation

3.2.1 Baseline functions

In order to verify the feasibility and effectiveness of the cross-border e-commerce logistics path optimization model solution algorithm IAGA designed in this paper, the six groups of benchmark functions selected include three groups of single-peak functions shown in Eqs. (24)~(26) and three groups of multi-peak functions shown in Eqs. (27)~(29):

(1) Bohachevsky function:

$$\begin{cases} f_1(x,y) = -x^2 - y^2 + 0.3\cos(3\pi x) - 0.3\cos(4\pi y) - 0.3 \\ x,y \in [-10,10] \end{cases} \tag{24}$$

(2) Rosenbrock function:

$$\begin{cases} f_2(x,y) = -100\left(y - x^2\right)^3 - \left(1 - x^2\right)^2 \\ x,y \in [-5.12, 5.12] \end{cases} \tag{25}$$

(3) Ackley's Path function:

$$\begin{cases} f_3(x,y) = -\left(-20\mathrm{e}^{-0.2\sqrt{0.5\left(x^2+y^2\right)}} - \mathrm{e}^{\sqrt{0.5(\cos 2\pi x + 2\pi y)}} + \mathrm{e} + 20\right) \\ x,y \in [-30,30] \end{cases} \tag{26}$$

(4) Multi-peak function:

$$\begin{cases} f_4(x,y) = x\cos(2\pi y) + y\sin(2\pi x) \\ x,y \in [-2,2] \end{cases} \tag{27}$$

(5) Schaffer's f6 function:

$$\begin{cases} f_5(x,y) = 0.5 + \dfrac{\sin^2\sqrt{x^2+y^2} - 0.5}{\left[1 + 0.001\times\left(x^2+y^2\right)^2\right]^2} \\ x,y \in [-10,10] \end{cases} \tag{28}$$

(6) Hansen function:

$$\begin{cases} f_6(x,y) = -\sum_{i=1}^{5} i \cdot cos\left[(i-1)x + i\right] \cdot \sum_{i=1}^{5} i \cdot cos\left[(i+1)y + i\right] \\ x,y \in [-10,10] \end{cases} \tag{29}$$

By testing the simulation of single-peak function and multi-peak function, and also comparing with the simulation results of AGA, the performance of IAGA can be reflected more comprehensively.

3.2.2 Simulation parameterization

In this simulation experiment, the AGA parameters are set as, the population size is 120. The memory bank capacity is 12. The number of iterations is 120. The crossover probability is 0.6. The variation probability is 0.09. The number of initialized population individuals M=120. The IAGA parameters are set as follows: adaptive control parameter k_1=0.80, k_2=0.65, k_3=0.25, and k_4=0.005, and the rest of the parameters are the same as those set in the AGA.

3.2.3 Simulation test results and analysis

The algorithms are randomly run 50 times, the best and worst values are selected as the criteria for evaluating the algorithms' values, the average value is used as the criterion for evaluating the algorithms' solution accuracy, and the standard deviation is used as the criterion for evaluating the algorithms' stability and robustness, and the results of the six groups of benchmark functions optimized using AGA and IAGA are shown in Table 1.

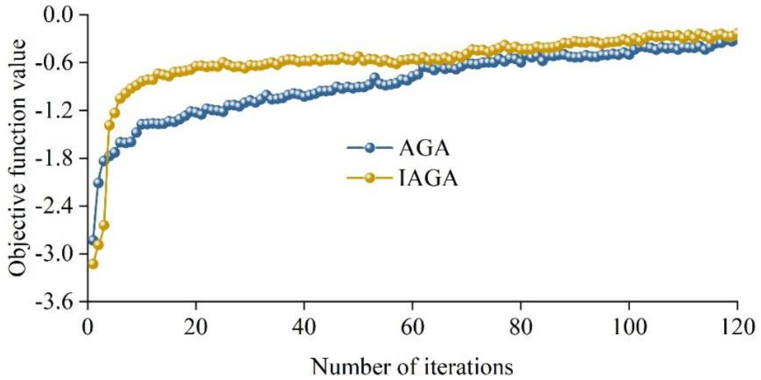
It can be seen from the data comparison that although the best value of both AGA and IAGA optimization is closer to the theoretical solution, the computational accuracy of IAGA is higher than that of AGA, and in the case of multi-peak function optimization, the worst value of AGA optimization performs poorly. This is because AGA optimizes the performance mainly by adjusting the crossover rate and mutation rate, but in complex problems, this adjustment may not be effective enough to maintain the diversity of the population and lacks the ability of dynamic adaptation. In terms of the average value of the optimization search, AGA optimization results differ greatly from the theoretical results, i.e., the optimization search often falls into local convergence and is difficult to jump out of it.IAGA greatly improves its spatial searching ability due to the introduction of the diversity of the immune system population as a marker of population evolution, and its average value of the optimization search is closer to the theoretical solution. In terms of the standard deviation of the optimization search, the stability of the optimization search as well as the robustness of IAGA is better than that of AGA.In summary, the optimization performance of IAGA is stronger than that of AGA in terms of both the quality of the solution and the convergence accuracy and stability of the algorithm.

Table 1: Simulation test results of the benchmark function

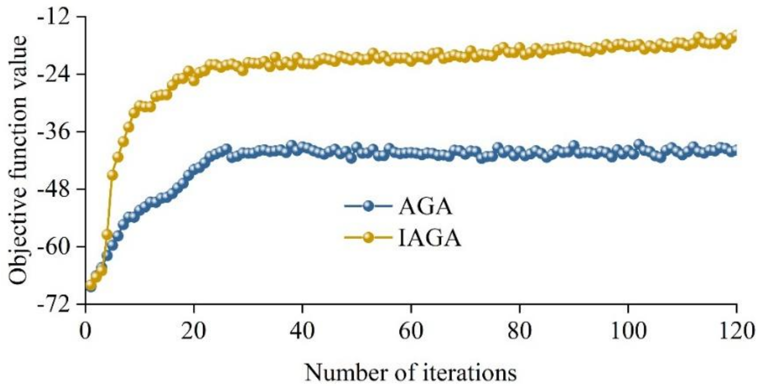
Function	Algorithm	Best value	Worst value	Mean	SD
f_1	Theoretical solution	-0.26	/	/	/
	AGA	-0.33	-2.43	-1.41	2.45E-2
	IAGA	-0.26	-0.21	-0.25	5.74E-5
f_2	Theoretical solution	0	/	/	/
	AGA	-0.44	-359.52	-237.83	49.61
	IAGA	-5.76E-3	-2.47E-2	-9.94E-3	4.67E-3
f_3	Theoretical solution	0	/	/	/
	AGA	-1.13	-3.61	-2.47	1.13
	IAGA	3.07E-3	4.09E-2	3.58E-3	2.05E-2
f_4	Theoretical solution	3.62	/	/	/
	AGA	3.55	1.41	1.72	1.72
	IAGA	3.59	2.64	3.14	0.56
f_5	Theoretical solution	1	/	/	/
	AGA	0.95	0.92	0.93	1.71E-2
	IAGA	1.01	0.95	0.98	5.35E-3
f_6	Theoretical solution	181.63	/	/	/
	AGA	168.02	160.71	163.57	6.41
	IAGA	181.12	177.38	179.86	2.09

In order to more intuitively reflect the optimization accuracy of the 2 algorithms as well as the convergence speed, the 6 groups of objective functions are compared by taking 50 random trials to select the results of an iterative process with the best optimization results. The Bohachevsky function and Hansen function are used as examples of single-peak and multi-peak objective functions, respectively, and the convergence process of the optimal value of the objective function in each generation and the average value of the objective function in each generation is shown in Fig. 4. Where, (a) and (b) are the optimal and average values of the Bohachevsky function and (c) and (d) are the optimal and average values of the Hansen function, respectively.

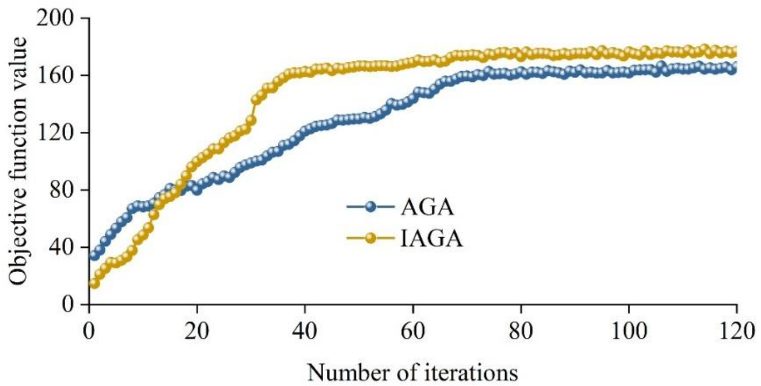
From the figure, it can be seen that the convergence accuracy and convergence speed of IAGA are better than that of AGA, which indicates that IAGA maintains good performance in solving single-peak function problems as well as multi-peak function problems.



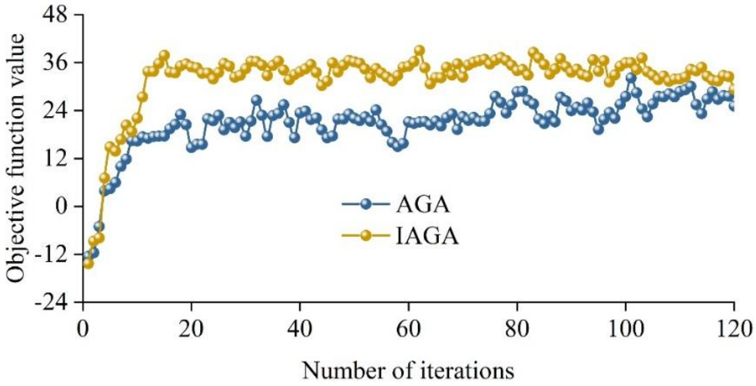
(a) The optimal values of each generation of the f_1 function



(b) The average value of each generation of the f_1 function



(c) The optimal values of each generation of the f_6 function

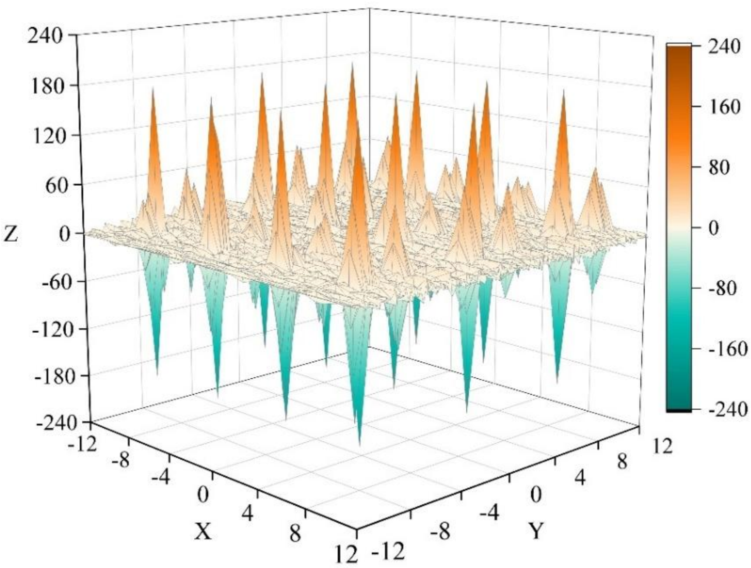


(d) The average value of each generation of the f_6 function

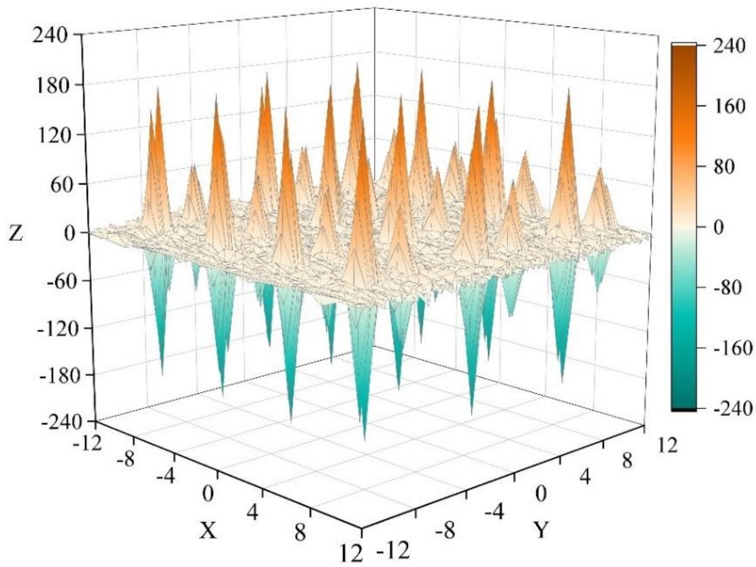
Figure 4: The convergence process of the optimal and average values of the objective function

In order to compare the global optimal finding ability and local optimal finding ability of the two algorithms, the optimal individuals of the two algorithms in the process of solving three sets of multi-peak functions for 120 iterations are counted, and the distribution positions of these individuals in the Hansen function are shown in Fig. 5, in which (a) and (b) denote the distributions in the AGA and IAGA, respectively.

It can be seen that AGA can only find part of the global optimum and local optimum, with certain limitations, and fewer extreme points are found, while IAGA can find almost all global optimums and local optimums, and more extreme points are found. From the comparison of these two points, we can clearly see that IAGA is significantly better than AGA, both in the global optimization ability and local optimization ability.



(a) AGA-Hansen function



(b) IAGA-Hansen function

Figure 5: Distribution map of the optimal individual in the function during 120 iterations

3.3 Analysis of optimization results of logistics network of enterprise A

In order to verify the effectiveness and feasibility of the improved adaptive genetic algorithm (IAGA) for solving the optimization problem of cross-border e-commerce logistics network, this paper takes the cross-border e-commerce logistics network of enterprise A as an example.

3.3.1 Relevant data

This paper selects ten sets of data in the actual operation of enterprise A through the actual research of enterprise A. It is used to verify that the established optimization model and the designed algorithm are feasible and effective for enterprise A. The optimization model and the designed algorithm are also used to verify the feasibility and effectiveness of the optimization model. These ten sets of data mainly include the weight and quantity of cross-border goods sold by 30 long-term cooperative core sellers to the same destination country, as well as the transportation unit prices between each node, the transportation durations between each node, the collection and handling capacity of regional distribution centers within China, the loading capacity constraints of flights, the commitment to transportation and delivery time, the penalty factors for violating the constraints of the commodity handling capacity of regional distribution centers within China, the penalty factors for violating the loading capacity constraints of flights, and the penalty factors for violating the commitment to transportation and delivery time constraints.

3.3.2 Experimental environment and algorithm parameterization

In this paper, the designed algorithm is run based on MATLAB simulation software version 2024b, and the cross-border e-commerce logistics network optimization problem is solved through MATLAB programming implementation, involving the parameter setting of the AGA algorithm and the parameter setting of the IAGA algorithm as shown in the previous section.

3.3.3 Comparative analysis of algorithm results

The first set of data and parameters are substituted into the cross-border e-commerce logistics network optimization model of enterprise A. The cross-border e-commerce logistics network optimization model of enterprise A is solved 15 times by AGA algorithm and IAGA algorithm respectively, and the results of the comparison of the two genetic algorithms are shown in Table 2.

Analysis shows that the optimal solutions of logistics cost objective function of AGA algorithm and IAGA algorithm in solving the cross-border e-commerce logistics network optimization model are 175894.36 yuan and 174217.83 yuan, respectively, and the value of the optimal solution using IAGA algorithm is smaller than that of the AGA algorithm. From the relative error values and relative error rates of the 15 groups of optimal solutions, the relative error values and relative error rates of the AGA algorithm and the IAGA algorithm in solving the optimization model of cross-border e-commerce logistics network are 3932.09 yuan, 1455.45 yuan, and 2.24%, 0.84%, respectively, and the values of the 15 groups of optimal solutions solved by using the IAGA algorithm are much closer to one another and have better stability.

Table 2: Comparison of model results solved by two genetic algorithms

Comparison item	Algorithm	
	AGA	IAGA
Maximum value	179826.45	175673.28
Minimum value	175894.36	174217.83
Average value	177639.24	175129.65
Optimal solution	175894.36	174217.83
Relative error value	3932.09	1455.45
Relative error rate	2.24%	0.84%

Since the Improved Adaptive Genetic Algorithm (IAGA) is improved on the basis of the Adaptive Genetic Algorithm (AGA) by introducing the immune system population diversity as a sign of population evolution, mainly in order to prevent the genetic algorithm from stagnating due to the emergence of the locally optimal solution and to improve the quality of the optimal solution solution, it is necessary to compare the convergence effect of the two algorithms and the quality of the optimal solution solution. A comparison of the convergence of the two genetic algorithms is shown in Figure 6.

It can be observed that the AGA algorithm converges to the optimal solution 175894.36 in the 90th iteration, while the IAGA algorithm should be able to converge to the optimal solution 174217.83 in the 218th iteration, and the convergence speed of the AGA algorithm is obviously faster than that of the IAGA algorithm, but it is easy to have the situation that the optimal solution is stagnant in the very beginning and the solution quality of the AGA algorithm is not as good as that of the IAGA algorithm. The solution quality of AGA algorithm is not as good as that of IAGA algorithm. The AGA algorithm is better than the IAGA algorithm in terms of the running time for finding the optimal solution.

In summary, the performance of IAGA algorithm in solving cross-border e-commerce logistics network optimization model is better than that of traditional AGA algorithm, and it can effectively solve the problem of stagnation of the optimal solution of traditional AGA algorithm, so the improved IAGA algorithm will be used in solving the cross-border e-commerce logistics network optimization problem of enterprise A.

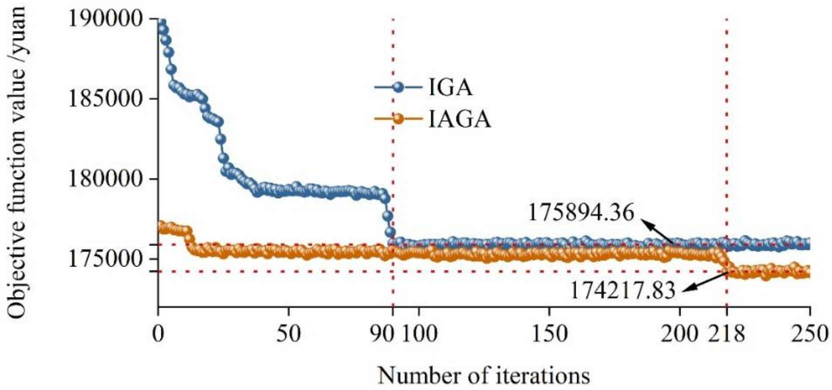


Figure 6: Comparison of convergence of two genetic algorithms

3.3.4 Solving and analyzing the optimized results

A total of ten groups of data and parameters are substituted into the cross-border e-commerce logistics network optimization model of enterprise A. The IAGA algorithm is used to solve the cross-border e-commerce logistics network optimization model of enterprise A. Each group of data is solved randomly for 15 times, and the results of the logistics cost objective function are shown in Fig. 7. Through analysis, it can be seen that the relative error rate of the 15 times solving results of these ten groups of data is not greater than 1.8%, indicating that the performance of the IAGA algorithm to solve the optimal solution is relatively stable.

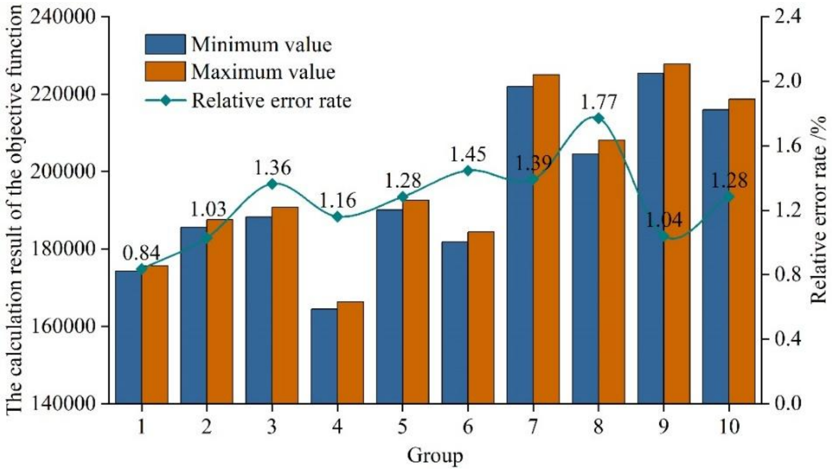


Figure 7: Calculation results of the model objective function solved by IAGA algorithm

The IAGA algorithm is used to solve the optimal transportation path of the model, and it is examined that all the cross-border merchandise transportation paths on the seller's side do not violate the constraints on the merchandise processing capacity of the regional distribution centers in China, the violation of the flight load constraints, and the violation of the promised transportation and delivery time constraints. The comparison results between the optimal solutions of the ten sets of data obtained by using the IAGA algorithm and the actual total transportation cost incurred by Enterprise A are shown in Table 3.

The comparison shows that the optimal solution of the total transportation cost obtained by using the IAGA algorithm to solve the model of cross-border e-commerce logistics network optimization problem of enterprise A is lower than the actual total transportation cost incurred by enterprise A. This model can effectively reduce the total transportation cost, which is expected to be reduced by 1% to 8%, thus reflecting that the IAGA algorithm has a better optimization seeking ability in solving the cross-border e-commerce logistics network optimization problem of enterprise A, and also It shows that the IAGA algorithm is feasible and effective in solving the cross-border e-commerce logistics network optimization problem.

Table 3: Comparison results between the optimal solution and the actual value

Data number	Optimal solution	Actual value	Difference	Differential rate /%
Group 1	174217.83	185342.73	-11124.90	-6.00
Group 2	185631.48	201583.69	-15952.21	-7.91
Group 3	188293.64	203768.74	-15475.10	-7.59
Group 4	164435.96	174592.71	-10156.75	-5.82
Group 5	190124.85	193485.13	-3360.28	-1.74
Group 6	181822.53	193647.24	-11824.71	-6.11
Group 7	221944.68	225961.85	-4017.17	-1.78
Group 8	204537.52	214862.76	-10325.24	-4.81
Group 9	225418.49	232594.38	-7175.89	-3.09
Group 10	215962.38	233715.14	-17752.76	-7.60

If Enterprise A adopts the IAGA algorithm to optimize its logistics network, it can not only effectively reduce the total cost of logistics and transportation and improve the efficiency of transportation, but also avoid the additional costs arising from unexpected situations, such as the labor costs of sorting operators arising from the surge in the volume of orders, so as to improve the competitiveness of the enterprise.

4 Conclusion

This paper takes the cross-border logistics network of countries along the “Belt and Road” as the research object, constructs a logistics network optimization model, designs the Improved Adaptive Genetic Algorithm (IAGA) as the model solution method, and verifies the validity of the model by taking Enterprise A as an example.

In the six function simulation experiments, IAGA is better than AGA in terms of solution quality as well as convergence accuracy and stability of the algorithm.Meanwhile, IAGA is better than AGA in terms of convergence accuracy and convergence speed, and it has better global optimization seeking ability and local optimization seeking ability. In the cross-border logistics network optimization example of enterprise A, the optimal solutions of the logistics cost objective function obtained by the AGA algorithm and the IAGA algorithm are 175894.36 yuan and 174217.83 yuan, respectively, and the relative error value and the relative error rate are 3932.09 yuan, 1455.45 yuan, and 2.24%, 0.84%, respectively, which indicates that the optimal solution value solved by using the IAGA algorithm is are closer and have better stability. In addition, the relative error rate of the IAGA algorithm in solving the ten sets of data of enterprise A is not greater than 1.8%, and the optimal solution of the total cost of transportation obtained is 1%~8% lower than the actual total cost of transportation incurred by enterprise A. This shows that the IAGA algorithm has a better ability to find the optimal solution in solving the optimization problem of the cross-border e-commerce logistics network of enterprise A. The algorithm is effective in reducing the total cost of logistics and transportation and improving the competitiveness of the enterprise. The IAGA algorithm can effectively reduce the total cost of logistics transportation and improve the competitiveness of enterprises.

Although this paper has achieved some results on the research of cross-border e-commerce logistics network optimization problem, there are still many aspects that need to be improved and perfected:

(1) IAGA algorithm in this paper in solving cross-border e-commerce logistics network optimization model optimal solution there is a certain range of fluctuations, in order to improve this fluctuation, the future can be more in-depth research on the optimization and improvement of genetic algorithms.

(2) The method of this paper is relatively single, in the future, we can explore the possibility of trying other optimization algorithms to solve the cross-border e-commerce logistics network optimization model, and explore to find the optimal solution algorithm.

(3) Due to the actual situation of enterprise A, some nodes and links are simplified when solving the optimization model of cross-border e-commerce logistics network, if there are conditions in the future, we will consider increasing these nodes to optimize the cross-border e-commerce logistics network in all aspects, so that the content of the research can be more adapted to the real world scenarios.

About the Author

Hong Su, a Master of Economics in International Trade from Dongbei University of Finance and Economics, specializes in cross-border e-commerce and international trade. She holds the CET-8 English proficiency certificate, Cambridge Business English Intermediate, and 1+X Cross-border E-commerce B2B Data Operations Intermediate Certification. She contributed to the development of cross-border e-commerce B2B data operations courses and mentored students to win three first prizes in the OCALE National Cross-border E-commerce Innovation and Entrepreneurship Competition. Additionally, she guided students to secure third prizes in the 2023 Shandong Provincial Higher Vocational Colleges Internet+ International Trade Competition. She has published multiple research papers on cross-border e-commerce and participated in three related research projects.

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